Impact of COVID-19 on fresh produce supply chains: Evidence from Pakistan

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Abstract

In this paper, we examine the effect of COVID induced lockdowns and compliance on the potato supply chain in Punjab, Pakistan. By combining granular price level information from various sources and primary survey data of more than a thousand farmers, we show that the middlemen were the clear winners in the supply chains during the time of COVID induced lockdowns. During COVID, the middlemen retained a higher share of prices, both upstream and downstream the vertical supply chain. Besides bearing the burden of reduced price-shares, we also show that the farmers that lacked market linkages and were dependent on unlicensed agents, were affected the most. This effect is accentuated when farmers receive additional services from middlemen such as credit and transport.

Introduction

In a survey conducted with 400 farmers across Punjab, about one-third of farm households reported a loss of earnings due to the pandemic (Yamano, Sato, & Arif, 2020) with disruptions in the supply chains identified as a major cause of declining incomes. This comes primarily due to the shortage of labor, mobility restrictions, and low market prices for farmers. However, a critical aspect that remains unclear is the role played by commission/wholesale agents during the pandemic to ensure uninterrupted supply to agriculture produce markets. Since their profits are contingent on this supply chain's continuity, it is unclear if they took steps to exploit the situation to reap higher profits, or if they facilitated the farmers to ensure the continuity of the supply. In this study we focus on the complete supply chain of potatoes, from the farmer to the wholesale markets to identify the role played by middlemen and how it impacted farmers and consumers during the pandemic. Specifically, the aim is to identify if they acted as facilitators or created encumbrances during the COVID lockdown.

Farming remains the predominant occupation and source of income for 48% of the population of Punjab, Pakistan. Recent studies have provided suggestive evidence on the exploitation of farmers by middlemen through low offer prices and informal loans (Rana, 2018; Haq, 2013). Agents that conduct the auctions push up the bid price for essential commodities leading to inflated retail prices and large welfare losses. Very little research has been done to investigate this influential position occupied by the different tiers of

middlemen in the agriculture supply chain in Pakistan. This study generates evidence on the facilitative or exploitive role played by middlemen during the pandemic.

In this paper, we unlock various administrative data sources to help track fresh produce supply chains in Punjab, Pakistan from the farmgate to the retail. These data sources will provide avenues to other researchers to work on issues related to supply chains in Punjab, Pakistan. We combine the administrative data sources with surveys of more than thousand farmers from three major potato growing regions of Punjab (Kasur, Depalpur, and Okara) to understand the market linkages and the challenges encountered by the farmers in marketing their produce. We also identify the different intermediaries through whom the farmers sell their produce. The survey was rolled out in collaboration with the local district administration. In this context, the village revenue officials (*'patwari'*) and the village headmen (*'numberdaar'*) played a key role in establishing the connection between the field teams and the farmers and ensuring high response rates.

Our results show that farmers' share of the auction price on average reduced by a significant 12 percentage points during COVID lockdowns while the middlemen were able to take advantage of the COVID related lockdowns by increasing their price share by on average 6 percentage points. The results show that the middlemen were able to negotiate better terms from both the farmers (by paying them less share of the auction price) and the retailers (by charging more of the share of the retail price) during the time of COVID related restrictions.

We find that it is the farmers selling outside the market that are negatively affected during the lockdowns. The farmers that could sell in the market (via licensed agent or self) did not experience a decline in the prices that they received. This could be due to the fact that farmers that sell in the market have better market linkages and are able to search for the best prices even during the time of lockdowns. In contrast, the farmers that sell to agents outside the market are probably more dependent on the respective agents and are therefore more susceptible to exploitation.

Farmers who sell to licensed agents outside the markets receive significantly lower prices than those who sell to unlicensed agents. Additionally, those who obtain additional

services[1] sell for lower prices than those who do not. In view of these findings, the farmers who are the worst off, are the ones who harvest during periods of lockdown, sell to licensed agents and obtain additional services. An interesting finding from our results is that the decrease in prices due to COVID related lockdowns was larger for the case of sales made to unlicensed agents outside of markets. This points to the fact that farmers who have lesser market linkages have a higher vulnerability than those who have access to the market via licensed agents.

Our revealed choice results are also consistent with this effect of lockdowns estimated from the data. Figure 1 shows that inadequate prices and difficulty in finding buyers were the predominant issues faced by the farmers during the COVID related restrictions.
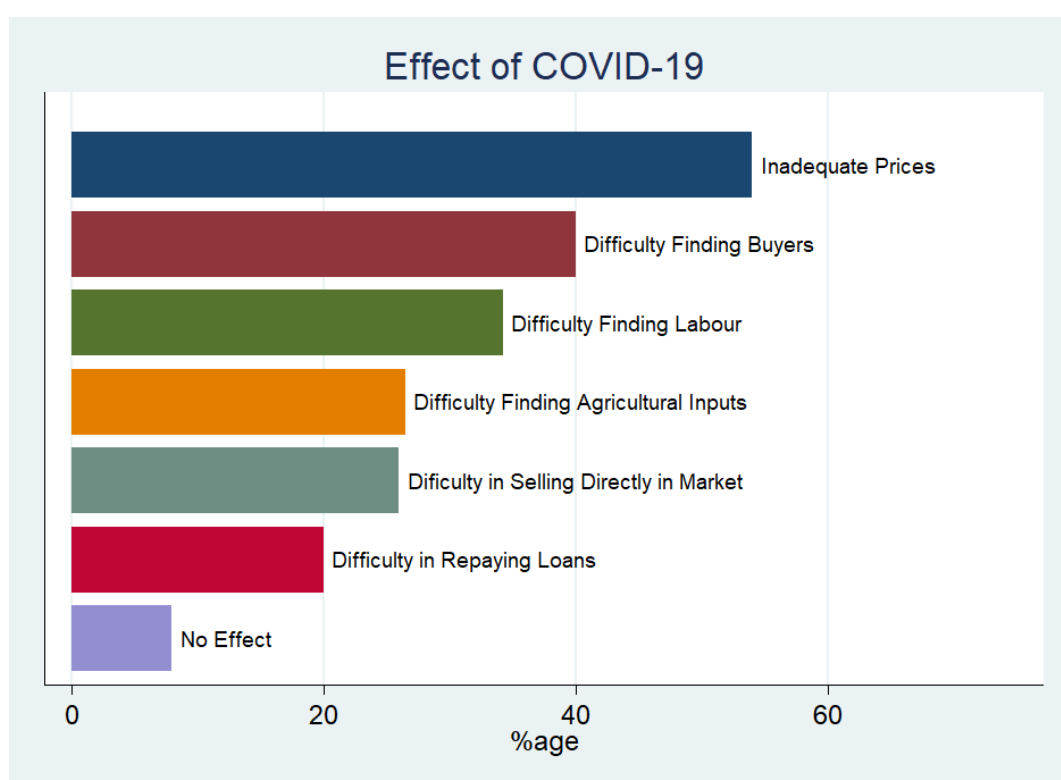

Figure 1: Farmers' reported effects of COVID-19

Our paper is most directly related to the limited literature on informal market exchanges in the context of developing countries. Ashraf et al (2009) show that larger markets tend to be inaccessible to a majority of small scale farmers and therefore they usually resort to selling to middlemen who operate in villages, and also accept the terms offered. This is

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[1] Such as credit, transport facility, warehousing/storage, help with purchase of inputs and so on.

consistent with our results. From amongst these village middlemen, we additionally find that farmers that sell to unlicensed agents are more susceptible to shocks such as COVID.

Our findings are also consistent with Atkins and Donaldson (2015) that shows that intermediaries earn a bulk of the profit whereas consumers and farmers are disadvantaged. One underlying reason for this is that wholesale markets are mostly inaccessible and especially for those farmers in remote locations. The usual implication is that consumers end up paying substantially higher for products, and that price gaps are significantly underestimated in such cases. This has welfare implications since consumers pay more for even basic necessities, which in developing countries such as Pakistan, can mean a lower standard of living. These claims of remote villages being exploited in terms of input and output prices have also been corroborated by Agarwal et al. (2018). There is significant variation in prices between the most remote and least remote villages, almost as much as a 40% gap in price in Africa. Furthermore, farmers from remote villages tend to depend more on village middlemen, and sometimes other farmers for purchasing agricultural inputs that are not easily available in the region. This most likely results in a bifurcated effect in the sense that while farmers can use inputs that they might not have access to otherwise, the downside is that these middlemen often tend to charge more which reduces earnings for farmers in the long run.

From what can be seen from literature, a major contributor to the vulnerability of farmers is lack of information. This information asymmetry is one main factor why farmers resort to only selling to middlemen in their villages. Therefore, recently, there has been focus on eliminating this gap in information by amplifying information that farmers have about middlemen outside their own community or villages. This arms farmers with knowledge about other options that could potentially pay more than their local middlemen, which serves as a deterrent for middlemen. This is to say that middlemen may be then inclined to reduce their profit share, which could potentially increase welfare for both farmers and consumers. However, as shown by Mookherjee et al (2018), increasing access to information inherently has no actual impact on farmgate prices since the effect can be bifurcated i.e. if farmers can potentially sell at higher prices, middlemen will buy at

increased rates and vice versa is also true. Therefore, policies that aim to mainly counter the information asymmetry tend to be counterproductive.

Background

Fresh Produce Supply Chains in Pakistan

Fresh produce supply chains in Pakistan, like in other developing countries, are complex and involve a chain of agents from the farmer to the final consumer. Whether or not the Pakistani farmer receives a competitive price for his produce is contingent on the overall design and architecture of fresh produce markets (FPMs), which serve as the primary link between producers and consumers of agricultural commodities in the country. FPMs are the physical locations where the majority of farmers deliver their produce personally or through a representative or a middleman for the purpose of auctioning/selling to other intermediaries, wholesalers, retailers, or end users. As a result, what occurs in these markets, how their operations are conducted, how various sellers and buyers' access is restricted or enabled, how much information about other markets is available, and other types of information asymmetry that can exist is rarely documented. What we see is a type of missing market and the information asymmetry is used as an exploitative tool for both consumers and farmers alike. This implies that middlemen often sell produce to consumers at higher prices all the while buying at lower rates from farmers, and thereby earning a high profit in the process. In the long run, this entire practice reduces welfare for the farmers and consumers, which can affect the standard of living and access to basic staples for some.

Figure 2 outlines a simplified flow of agricultural supply chains for a typical small farmer in Pakistan. The supply chain starts with the farmer procuring inputs and land (if tenant). Since such farmers are typically credit constrained and they rely on various agents to meet their liquidity needs. Once farmers produce the output, it is sold to one of these agents. For the purpose of this paper, we categorize these agents as follows:

1. Licensed Agent or 'Paaca Aarti' is an agent responsible for auctioning the produce in the government regulated markets (called market committees).
2. Non-Licensed Agent comprises 'Kacha Aarti' or 'Beopari'.
   a. 'Kacha Aarti' is an agent who buys produce from small farmers and sells it to other middlemen or in the market.

b. 'Beopari' is an agent who buys produce from farmers or other middlemen typically when the price is low and sells in the market when the price is high.

After the produce is auctioned in the wholesale market, it is then sold by *pharias*, who are agents that break the auctioned produce into smaller units to be sold to retailers. Retailers include big supermarkets as well as street vendors from where the consumers buy the produce.
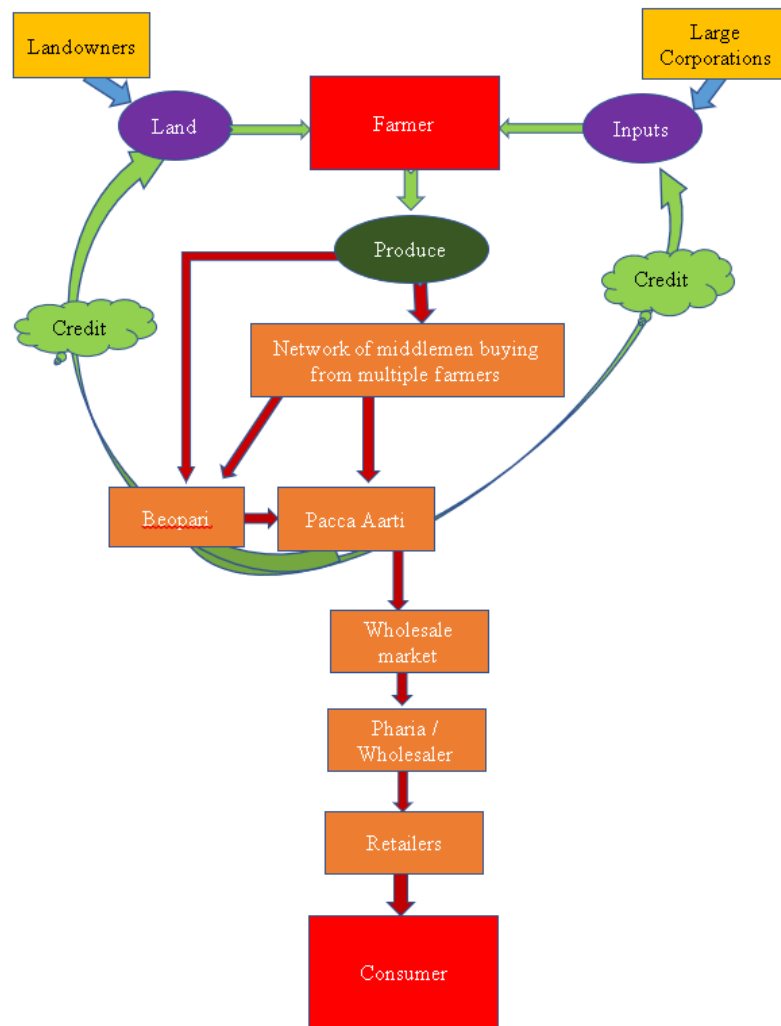

Figure 2: Fresh produce supply chain for a typical small-scale farmer

COVID in Pakistan

In our discussion on the COVID experience in Pakistan, we specifically focus on daily COVID cases, government interventions and the compliance with COVID restriction for the two year period from March 24, 2020 to April 10, 2022.

The very first case of COVID-19 was recorded in Sindh on 26th February 2020. On the 2nd of March, Pakistan officially closed its border with Afghanistan. On 11th March

2020, 76 new cases were reported in different areas of Punjab. The first lockdown was imposed on 24th March 2020 in Punjab and throughout the country on 1st April 2020 Though testing capacity was limited at that stage, a total of 972 cases were confirmed nationwide. The first full lockdown lasted until 9th May 2020, at which point the government eased restrictions in view of the potential detrimental economic impact. This brought about the concept of 'smart lockdown'[2], which was implemented at different points for the duration under consideration.

We present some of this information more formally for the case of the major cities of Punjab in Figure 3[3]. To generate the figure, the researchers have relied on the information that was available through the Department of Health, Government of Punjab[4] and the World Health Organization (WHO)[5] country-level reports on COVID.

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[2] In the case of Pakistan, 'smart lockdown' refers to a locality-based approach in imposing restrictions only in high risk areas to slow down the growing positivity rate. This is accompanied with limited business hours, strict weekend curfews, and enforcement of other precautionary measures. Only essential services providers such as pharmacies and grocery stores are allowed to operate. For this report, we use the terms 'smart lockdown' and 'partial lockdowns' interchangeably.

[3] The cities covered include Lahore, Faisalabad, Gujranwala, Rawalpindi, Multan, Sargodha and Sialkot. We restrict ourselves to these districts since data for other cities of Punjab is unavailable and also because a subsequent section focuses on these districts for an analysis of supply chains during COVID.

[4] To construct the lockdown periods, official government announcements made through various media platforms were used.

[5] These reports are available publicly for Pakistan at: [http://www.emro.who.int/pak/information-resources/pakistan-covid-19-situation-reports.html]. Besides providing broad national level statistics, each report gives disaggregated city-level data for the major cities of Pakistan.
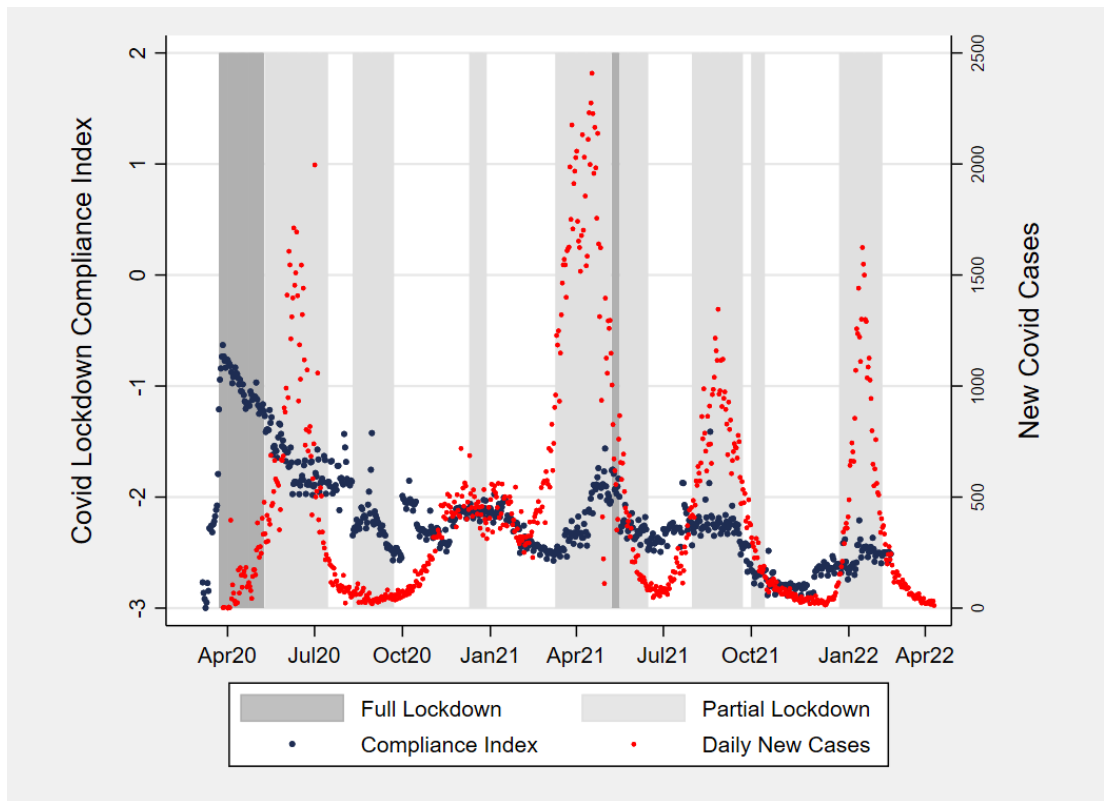
Figure 3: New Covid Cases and Covid Lockdown Compliance Index Timeline for

Punjab

In this figure complete lockdown and partial lockdown periods are represented by dark and light gray regions during the period March 24, 2020 to April 10, 2022. Each red point is the total new daily cases aggregated across the covered major cities as measured by the y-axis on the right. The blue trend line is a daily composite index that has been created by aggregating the stringency index of government interventions and the degree of compliance as indicated by Google community mobility reports[6]. A higher value on the left y-axis implies that the stringency of announced measures was high *and* the extent of compliance with these measures was also high.

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[6] The Google Community Mobility data relies on real-time visitor counts based on the GPS locations of individuals who use Google services. One caveat is that this data does not capture those individuals who either do not carry a smartphone or do not utilize Google services. For more discussion on this and details on the construction of the index using these data see Appendix B.

This graph shows that the major urban areas under consideration have experienced four major and one minor COVID waves as indicated by the spikes in the red line[7]. Lockdowns also generally overlap with the same time-periods as a rise in the number of new cases was one of the key considerations for imposing them. We also note that the composite index saw increases during times of lockdowns but the overall trend is declining over time[8]. This means that measures installed by the government were also relaxed over time and consumer mobility also increased.

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[7] Note that the low number of new cases at the start of April, 2020 was most likely not because there were actually fewer cases but because the state machinery had not yet created reliable reporting mechanisms that could aggregate data.

[8] The increase is attributable to a rise in the stringency of the measures, rise in compliance with the measures or both. Similar trends disaggregated by city have been presented in Appendix B

Data

The data used in this study has been gathered from a variety of sources. One of the contributions of this paper is the unlocking of these data sources that can facilitate further research on related topics for Pakistan. These data sources are not otherwise known or easily available to researchers and their acquisition was possible only after obtaining special permissions and employing personal connections in the bureaucracy.[9]

Date Sources

<u>Harvest Price Survey</u>**:** The harvest prices survey is an annual survey conducted by the crop reporting service wing of the Agriculture Department Punjab. Harvest price is what is received by the growers at the time of harvest or within 2 months after the harvest of a crop in the villages where these are grown. Harvest prices are collected by the staff of Crop Reporting Service to determine the price level at the Farm Gate. This primary data of the survey is not available publicly, we could access the primary data through the Department of Agriculture. The data includes yearly detailed crop information of sampled farmers such as longitude/latitude of the land the crop is grown on, crop variety, crop cultivation and harvest date, amounts of fertilizers used on each land, harvest prices, and farmer names with contact numbers. For the purpose of this research, we obtained the data for potatoes for the years 2019 to 2021.

<u>Agriculture Marketing Information Service (AMIS):</u> is a publicly available information service managed by the Directorate of Agriculture (Economics & Marketing) Punjab. It provides daily auction prices of agriculture commodities from 135 markets across Punjab. AMIS also provides the daily record of supply of commodities from the origin in Pakistan (called arrival source) to destination in Punjab. We scraped daily data on auction prices and arrival sources for potatoes for the years 2019 to 2021.

<u>Decision Support System for Inflation (DSSI)</u>: has been developed by the Pakistan Bureau of Statistics (PBS) for monitoring of prices of various commodities, its trends and

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[9] One of the investigators on this project is also a bureaucrat belonging to the Pakistan Administrative Service (PAS) group of the Federal civil services of Pakistan.

improving governance. The DSSI is designed to facilitate policymakers, national price monitoring committees, provincial governments and district administration for price monitoring, improving governance and informed decision making regarding inflation. Weekly retail price information was obtained through this system.

Mouzza Census 2020: Is a complete census of the *mouzzas* (villages) of Pakistan undertaken by the Pakistan Bureau of Statistics (PBS). Through this exercise key information on cultivation practices, major Crops, natural resources, infrastructure, socio-economic indicators and data on *Abadi Deh* (community settlements) are collected for each village. It must be pointed out that this is not a household enumeration and survey exercise. Though this Census is supposed to be conducted every five years, the most recent census has been completed after a considerably long hiatus.

Farmer Survey: To supplement findings from the administrative data, we conducted a survey of 1060 potato farmers from 90 different *mouzzas* (villages) in the districts of Kasur, Okara and Lahore. The purpose of the survey was to collect detailed information on output and sale transactions, impact of COVID and technology adoption for potato farmers. Okara, Kasur and Lahore were selected based on the supply sources for the Lahore Fruit and Vegetable agriculture produce market (*Badami Bagh Mandi*)[10].

We used the *Mouzza* Census 2020[11] to identify the villages from these districts where cultivation of vegetables had been recorded. These villages were then matched with those where the harvest price survey[12] had been conducted to document the cultivation of potatoes. The intersection of villages was then divided into three size categories by total

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[10] This market is the largest agriculture produce market by transaction volume in Pakistan and plays an important part in the economic well-being of farmers and middlemen. Almost all the supply of fresh produce items that come to Lahore district are routed through this market. This market is also being studied in greater detail in a parallel study being conducted by the researchers to generate data on the wholesale market to retail part of the supply chain. The data collected on farmers will be used to further highlight the linkages in the supply chain.
[11] This is a detailed village level survey conducted by the Pakistan Bureau of Statistics. This data is not publicly available at the time of writing the report and has been obtained from the PBS after acquiring special permissions.
[12] This survey has been conducted every year since 2018, for onions and potatoes by the Crop Reporting wing of the Department of Agriculture, Government of Punjab.

cultivated area in each village. Finally, a random sample was drawn stratified by Tehsil and size category. Table 1 gives a detailed breakup by region.

District	Okara	Lahore[13]	Kasur	Total
Tehsil	3	2	3	**8**
Mouzza	56	3	31	**90**
Farmers	659	16	385	**1060**

Table 1: Number of Tehsil, *Mouzza,* Farmers reached during primary data collection

Identification of farmers within each village presented a unique challenge since there is no central database or record from where farmers could have been selected. Also, unlike a household survey, which is conducted door to door in the built up area in a village, it is not possible to easily identify farmers since most of them are out in their fields. To ensure a high response rate, the researchers engaged the local district administration for all three districts for help during the fieldwork. Potato farmers were gathered at a central location within each village where the research team met with them and conducted the surveys. To accomplish this task, the *patwari* and the *numberdaar[14]* played a key role in identification of potato farmers and in ensuring their presence at the gathering point[15].

Google COVID-19 Open Data repository: We also construct a population COVID compliance index by utilizing the Government Response Tracker dataset and the Regional Mobility Reports available on the Google COVID-19 Open Data repository.

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[13] It will be noted that the number of villages selected for Lahore District is very low. This is because agriculture in the district has dwindled over the past 10 years due to rapid urbanization and aggressive expansion of housing. Most landowners have sold their land to real estate developers.

[14] The *patwari* is a low-ranking government official who is in charge of maintaining records of land ownership and crops for multiple villages. The *numberdaar* or village headman is not a government employee but a person of influence in the village who is also an owner of land in that same village.

[15] One issue with this mechanism is that there can be selection bias in that the revenue official and the village headman gathered only a certain type of potato farmers from the village. To reduce this selection bias, the research team also had public announcements made in each village through mosques to encourage participation of farmers.

This index allows the researchers to see how daily reported daily cases varied with the COVID related measures[16].

Description of Data

In this subsection we describe the broad patterns in the data from the sources above. We combine the three sources (Harvest Price Survey Data, AMIS Data, and DSSI data) to provide comparison of per kilogram prices received by farmers, middlemen, and the retailers in Figure 4. The red vertical line indicates the start of COVID. We note that there is a clear wedge between the three prices with farmers getting, on average, less than half of the retail price. Furthermore, after COVID started spreading in Pakistan, we see a steep decline in all three prices followed by gradual recovery after July, 2020.
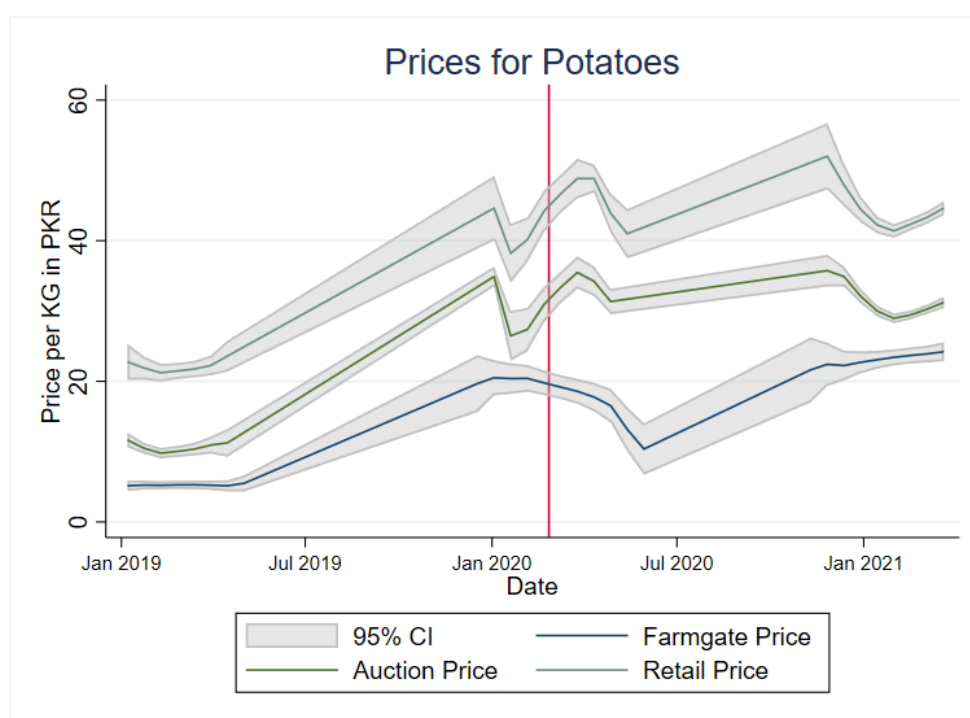

Figure 4: per KG Prices received by Farmers, Middlemen, and Retailers

We present the average yearly volume of potato supply by the arrival source in Figure 5 and average yearly sale by region in Figure 6. Okara is the biggest supplier of potatoes as well as seller of potatoes in Punjab.

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[16] For more discussion on this and details on the construction of the index using these data see Appendix B.
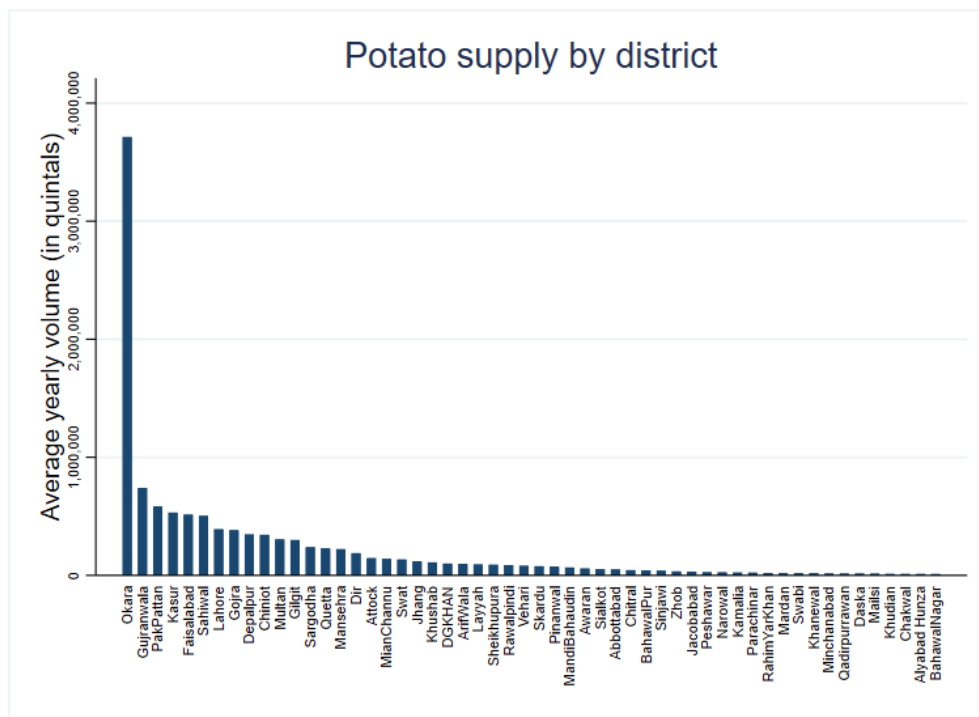
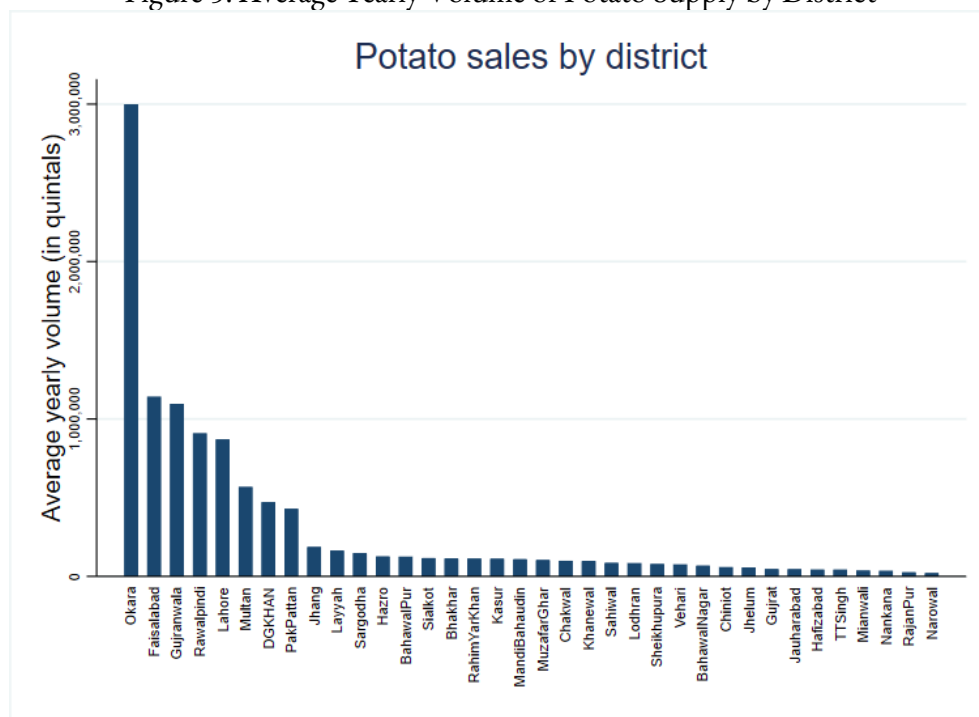Figure 5: Average Yearly Volume of Potato Supply by District

Figure 6: Average Yearly Volume of Potato Sales by District

Methodology

In this section, we outline the main methodology of the analysis. The paper first tries to identify the broad trends in the potato supply chain due to COVID lockdowns and mobility restrictions. Then an attempt is made to present more granular analysis to understand the farmer-middlemen interaction in the supply chain.

The two two main questions, therefore, explored in this paper are:

1. What was the impact of COVID related restrictions on various agents in the supply chain of potatoes?

2. What was the impact of COVID related restrictions on per unit prices received by potato farmers and how that varies with farmers' market linkages?

To answer the first question, we rely on administrative data and examine how price shares of farmers and middlemen are affected due to COVID related restrictions. We construct the relevant variables by combining information on farmgate, auction and retail prices from the harvest price data, AMIS auction data, and DSSI data, respectively. The farmgate-auction price ratio is a bi-weekly variable since farmgate prices are not available for exact dates but correspond to two week periods. The COVID lockdown timelines for the key districts have been compiled using official announcements from the National Command and Operation Center in conjunction with public information from the Department of Health, Government of Punjab.

Examining price shares inherently control for other factors that may commonly affect the prices in the numerator and the denominator and therefore the specification does not require controls for the economic conditions.

To estimate how COVID related restrictions affected farmers' share of auction prices, we estimate the following model:

$$FS_{sdt} = \gamma_0 + \gamma_1 COVID_{dt} + \mu_{dt}$$

FS_{sdt} is the share of prices received by farmers in destination d at time t from the source s, with, $FS_{sdt} = \frac{Farmer\ Price_{st}}{Auction\ Price_{dt}}$. Since farmer's produce is supplied to multiple

destinations, we use data on arrival sources (explained above) to determine the destinations that are fed by the source s. $COVID \in [Lockdown, Compliance]$ We separately estimate the above model with lockdown and compliance as the predictors. μ_{dt} is the error term. In this specification, our main coefficient of interest is γ_1 that captures the effect of lockdown or compliance on farmer share of the auction price under the assumption that the COVID restrictions are exogenous to μ_{dt}.

To estimate how COVID related restrictions affected middlemen share of retail prices, we estimate the following model:

$$MS_{dt} = \gamma_0 + \gamma_1 COVID_{dt} + \mu_{dt}$$

MS_{dt} is the share of prices received by middlemen in destination d at time t, with, $MS_{dt} = \frac{Auction\ Price_{dt}}{Retail\ Price_{dt}}$. $COVID$ and μ_{dt} are as defined above. In this specification, our main coefficient of interest is γ_1 that captures the effect of lockdown or compliance on middlemen share of the retail price under the assumption that the COVID restrictions are exogenous to μ_{dt}.

To answer the second question, we rely on the survey data of potato farmers (data source explained above) and estimate the impact of lockdowns on prices received by the farmer. The empirical specification we use is

$$p_{ijt} = \beta_0 + \beta_1 Lockdown_t + \beta_2 X_{it} + \epsilon_{ijt}$$

p_{ijt} is the price received by farmer i from buyer j (licensed agent, non-licensed agent, or firm) at time t. Lockdown is an indicator variable that takes a value 1 if there is lockdown at time t. X_{it} is the vector of controls such as produce quality, farmer experience, farmer size, and month fixed effects (to control for seasonal variation in prices). ϵ_{ijt} is the unobserved error term. In this specification our main coefficient of interest is β_1 which gives the average effect of lockdown on farmer prices under the assumption that lockdown is exogenous to ϵ_{ijt}.

Results and Analysis

In this section, we outline the results by breaking them into three subsections. In the first subsection we examine the overall impact of COVID related restrictions on price shares received by the farmers and middlemen. This helps us understand how various agents in the supply chain were affected due to COVID. This is followed by an examination of the upstream chain where we study the effect on prices received by the farmers and how that varies with market linkages of the farmers. In the final subsection, we dig deeper into the effect on farmers based on the type of middleman they interact with and the degree of dependence.

Overall Effect of COVID on Supply Chain

As explained earlier, the COVID lockdowns may lead to disparate incidence on various agents. Figure 7 presents the share of prices received by farmers (of auction price) and middlemen (of retail price). The figure exhibits a steep decline in the farmer share after the first case of COVID was identified in Pakistan while the middlemen share slightly increased after the COVID.
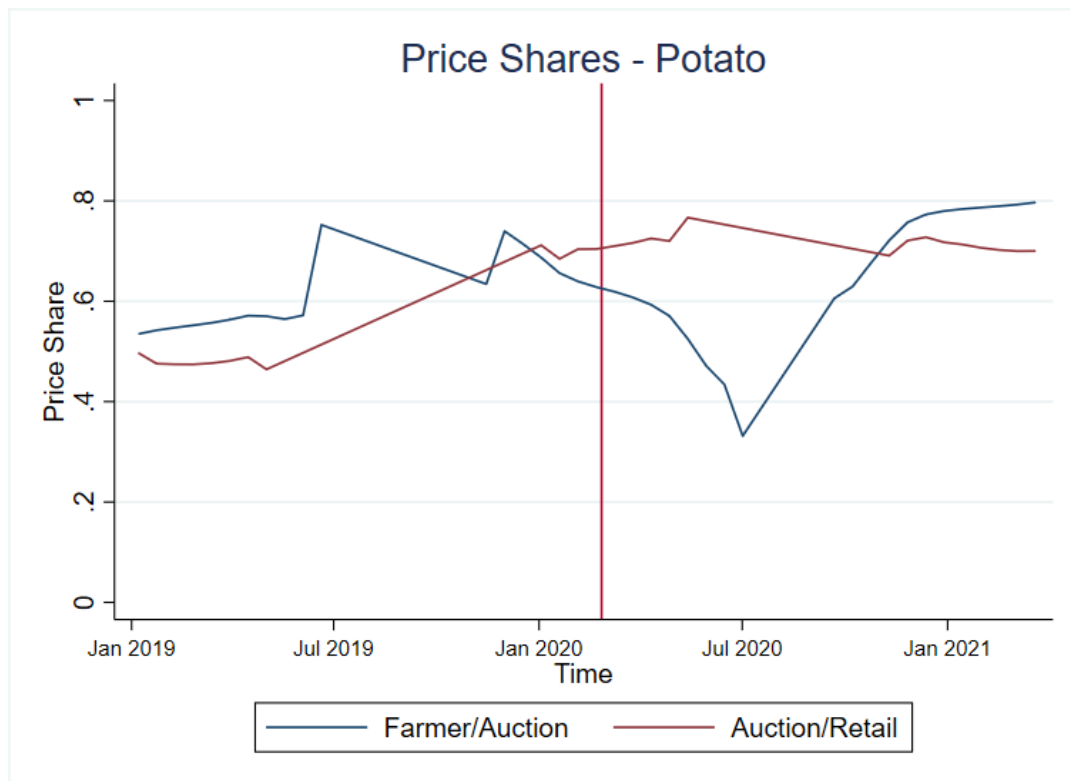

Figure 7: Potato Price Shares Timeline

To tease out the impact of COVID related lockdowns and compliance on price shares we report regression results in Table 2. Column 1 of Table 2 shows that farmers received 57 percent of the auction price on average which reduced by a significant 12 percentage points during COVID lockdowns. The compliance of COVID also had an effect on farmers with their share of auction price declining by approximately 10 percentage points (a statistically significant estimate) with every percentage increase in the compliance (column 2). This implies that farmers were clear losers in the supply chains during COVID.

	(1)	(2)	(3)	(4)
	Farmer/Auction	Farmer/Auction	Auction/Retail	Auction/Retail
COVID Lockdown	-0.119* (0.0457)		0.0614* (0.0262)	
COVID Compliance		-0.953** (0.285)		0.763*** (0.146)
Constant	0.565*** (0.101)	0.627*** (0.103)	0.654*** (0.0162)	0.604*** (0.0182)
Source Effects	Yes	Yes	No	No
Observations	100	81	100	81

* p<0.05 ** p<0.01 *** p<0.001. Standard errors in parentheses
Table 2: Potato Price Share Regression Results for Farmer/Auction and Auction/Retail

Middlemen, on the other hand, were able to take advantage of the COVID related lockdowns and compliances by increasing their price shares. Column 3 shows that middlemen were able to increase their price share of retail price by six percentage points (statistically significant) during lockdowns from the baseline share of 65 percent. The compliance had an even larger effect with middlemen share increasing by approximately 8 percentage points for every percentage increase in compliance. The results show that

the middlemen were able to negotiate better terms from both the farmers (by paying them less share of the auction price) and the retailers (by charging more of the share of the retail price) during the time of COVID related restrictions.

Effect of COVID by Farmers' Market Linkages

The above results show that the middlemen were able to relatively improve their market shares from both the upstream and downstream chains during the COVID related restrictions. We now examine the upstream part of the supply chain to see if the effects of COVID induced restrictions were different based on farmer's characteristics such as how connected the farmers are to the markets. This is an important investigation as it will help us understand the factors that enable farmers to better manage the effects of shocks such as COVID. For this purpose, we rely on our primary data gathered from potato farmers in the three potato growing districts of Punjab. In Table 3 we analyse the effect that the lockdown had on the per kilogram price received by the farmer when selling to three types of buyers: sale to non-licensed agents, sale in markets[17], and sale to firms.

Variables	(1)	(2)	(3)
	PerKgValue-Out of Market	PerKgValue-Market	PerKgValue-Firm
Lockdown	-1.790***	1.061	4.037
	(0.593)	(1.091)	(3.035)
Experience	0.0242	0.000201	-0.0174
	(0.0204)	(0.0282)	(0.123)
TotalAreaOwnership	0.00675**	-0.000969	-0.00438
	(0.00278)	(0.0118)	(0.0255)
Constant	21.55***	20.22***	23.15***
	(0.717)	(1.024)	(3.720)
Observations	2,255	783	81

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[17] A sale in a fresh produce market can be through an auction conducted by a licensed agent or by the farmer himself. In either case it indicates availability of market access to the farmer.

Potato Quality	Yes	Yes	Yes
Season Effect	Yes	Yes	Yes

*** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses

Table 3: Regression Results for Lockdown and per Kilogram Prices of non-licensed agents, Market, and Firm

Column 1 in table 3 shows the effect of COVID lockdowns on farmers who sold outside the market (to either licensed or non-licensed agents) whereas Columns 2 and 3 show the same estimation results for those farmers who made sales in markets and to firms, respectively. From these results we can see that the farmers who sold outside the market received a price that was Rs. 1.8/kg lower due to COVID lockdowns, after controlling for farmer characteristics, produce quality and seasonal variation. This result is also statistically significant. Columns 2 and 3, however, reveal that a similar loss was not suffered by farmers with access to markets and firms. While these coefficients are positive, they are not statistically significant, therefore we do not interpret this as a positive effect of COVID on the respective per unit prices from these buyers.

In combination with the results from the first subsection, the results of this subsection suggest that it is the farmers selling outside the market that are negatively affected during the lockdowns. The farmers that could sell in the market (via licensed agent or self) did not experience decline in the prices that they received. This could be due to the fact that farmers that sell in the market have better market linkages and are able to search for the best prices even during the time of lockdowns. In contrast, the farmers that sell to agents outside the market are probably more dependent on the respective agents and are therefore more susceptible to exploitation. We investigate this in more detail in the next subsection.

Effect of COVID and Farmers' Dependence on Middlemen

We now examine in detail the effects of lockdown on farmers' prices for the case where produce is sold outside of FPM. We look at how this effect changes with the type of middleman and the extent of farmer dependence on him as measured by the services obtained by the farmer.

Figure 8 shows the services provided by the middlemen to farmers in our sample of potato farmers. As the figure indicates, 31 percent of the potato farmers reported that no services are provided to them by their agents. Inputs and Credit are the most reported services by the farmers (31 and 33 percent respectively). Meanwhile, Advice on agricultural practices and provision of storage are the least reported services by the potato farmers[18].
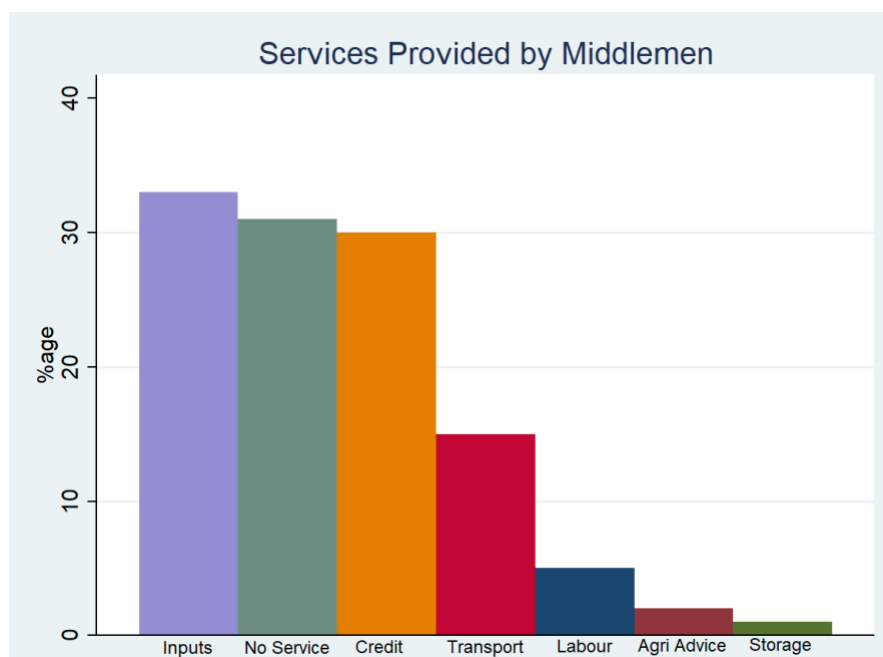

Figure 8: Services Provided by Middlemen to Potato Farmers

While we can see that inputs, credit and transport are services sought most frequently, for our empirical estimation we do not break the services up into their components but instead rely on a binary specification that indicates whether at least one or more service was obtained.

Table 4 presents the results of this estimation. As mentioned earlier, this is the case where farmers make sales outside of markets with the added dimension of type of middleman and whether any service was received. There are two types of middlemen buying directly from farmers outside of fresh produce markets (FPM): unlicensed agents and licensed agents. The difference between the two is that the latter can conduct auctions in FPMs whereas the former cannot.

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[18] Multiple services can be obtained by the same farmer.

Variable	PerKg Value
Lockdown=0, Licensed Agent=0, Services=1	-4.391***
	(0.877)
Lockdown=0, Licensed Agent=1, Services=0	-6.140***
	(0.796)
Lockdown=0, Licensed Agent=1, Services=1	-7.610***
	(0.700)
Lockdown=1, Licensed Agent=0, Services=0	-4.472***
	(1.203)
Lockdown=1, Licensed Agent=0, Services=1	-6.368***
	(1.636)
Lockdown=1, Licensed Agent=1, Services=0	-6.405***
	(1.352)
Lockdown=1, Licensed Agent=1, Services=1	-8.565***
	(1.116)
Experience	0.0480**
	(0.0216)
Total Area Ownership	0.00536
	(0.00689)
	26.89***
	(0.886)
Observations	1808
Potato Quality Effects	Yes
Seasonal Effect	Yes

*** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses

Table 4: Regression Results for Lockdown, Service, per Kilogram Prices of

Licensed/non-licensed agents

We first discuss what happens in periods when there is no lockdown. The results indicate that farmers who sell to unlicensed agents but receive a service[19] get Rs 4.39/kg less compared with those farmers who sell to unlicensed agents but do not receive any service. On the other hand, when no services are received but sales are made to a licensed agent the price received is Rs. 6.14/kg lesser than the price received from an unlicensed agent. Within sales to licensed agents, when services are received this value falls by an additional Rs. 1.5kg. This means that licensed agents offered a price that was considerably smaller than that offered by unlicensed agents.

In the presence of lockdowns, the price received from sales made to unlicensed agents when no services are provided is Rs. 4.47/kg lower than the base case. This value implies that lockdowns alone had a large impact. This effect is larger for the case when an unlicensed agent also provides services (-6.36/kg, which is Rs. 2/kg less the price of Rs. 4.39/kg, discussed previously). Looking at licensed agents who did not provide services, the reduction in price due to lockdown is Rs. 0.26/kg (Rs. 6.40/kg – Rs 6.14/kg). Licensed agents who did provide services, the price fall is larger Rs. 0.96/kg (Rs. 8.57/kg – Rs. 7.61/kg).

We note from these results that the licensed agents generally buy from farmers at prices that are much lower than those offered by unlicensed agents. This holds regardless of lockdowns and service provision. However, the change in prices due to COVID restrictions is higher for unlicensed agents. This trend also holds whether or not services were provided.

A potential reason for this result might have to do with the market power of licensed agents who play the dual role of commodity trader (*beopari*) and auctioneer (*aarti*) in the fresh produce markets. Such agents could arguably have stronger linkages in the markets as well as upstream in the supply chain through relationships with government officials and other influential persons in villages from where the produce is sourced. Further, they

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[19] We do not account for intensity of service provision but just whether they received at least one or more service from the ones shown in Figure 8.

are more likely to have better cash flows, and could take advantage of obtaining more favourable contractual terms in advance of the harvest period from farmers. In such transactions, since the agent is also sharing the risk of the commodity[20], we can think of this as an insurance mechanism with the premium built into the offer price. All of these statements, however, require further research to disentangle the reason for the observed results.

The finding that the dependent farmers fared worse during COVID is also corroborated by the qualitative data gathered from the farmers. In Figure 9 below we see that a vast majority of the farmers in our sample reported being exploited by the middlemen to receive lower prices for their crops. This finding is consistent with farmers' response in Figure 10 where a significant percentage of farmers reported receiving inadequate prices and difficulty in finding buyers. This is unsurprising since tringent lockdown measures entailed movement restrictions between cities, and in more extreme cases even within cities and closure of restaurants, retail markets, and other places of business.

Role of Middleman During COVID-19

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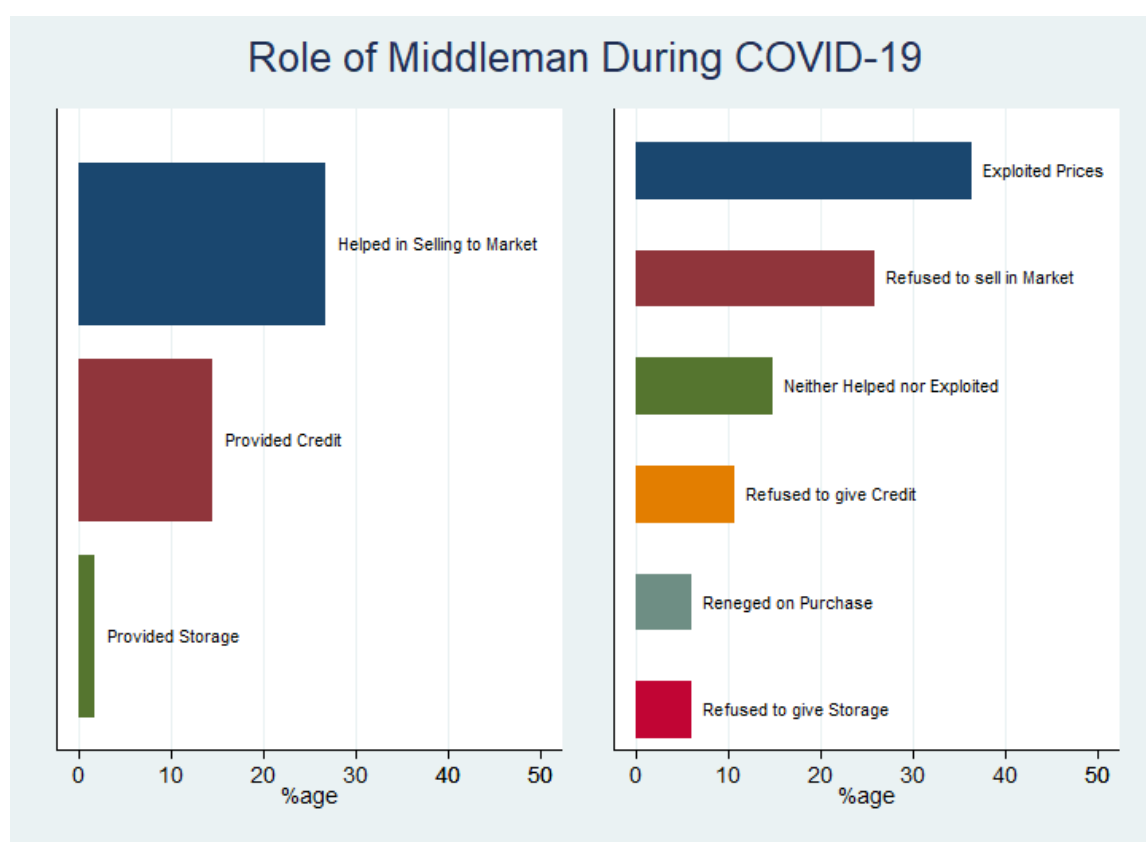
[20] As he is purchasing in advance of harvest he is subject to the same risks as the farmer, such as pests, flooding, water shortage.

Figure 9: Role of the Middleman for Potato Farmers during COVID-19

Figure 10 also highlights other issues that affected farmers during these troubled times. The most common problems reported after inadequate prices and difficulty finding buyers are related to inputs to production.
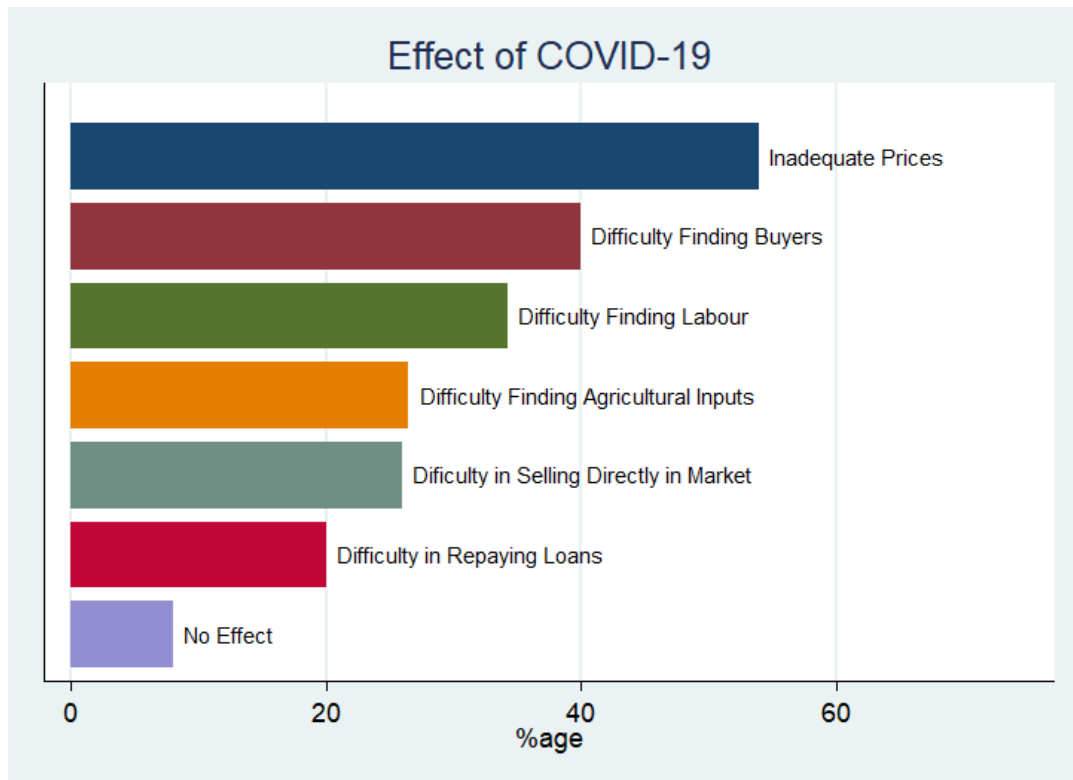

Figure 10: Effect of COVID-19 on Potato Farmers economically

Conclusion

COVID disrupted economies all over the world. In this paper, we examined the effects of COVID related restrictions on supply chains in the developing country context of Pakistan. We focused on potato supply chains in Punjab, Pakistan and examined the effects on the prices received by the players. We find disparate effects of pandemic on various agents in the supply chain. In particular we find that middlemen are able to exploit the pandemic conditions to their advantage by keeping a higher share of retail prices while passing on a lower share of auction prices to the farmers.

From the policy perspective, our research highlights that middlemen play an important role in the potato supply chains and are the essential link in determining welfare for consumers and incentives for producers. Any attempt at ensuring price stability must begin by ensuring that middlemen are not playing an exploitative role. In addition, ensuring better prices for farmers will improve agricultural productivity as they would have a significant incentive to innovate.

Our research further highlights that it is not only the licensed commission agents in the wholesale markets that play an important role for determining consumer and producer surpluses, rather it is the unlicensed middlemen such as *beopari* and *kacha aartis* that are equally important in the upstream supply chain. As a future agenda of this research, we are further investigating the nature of the role played by agents outside the regulated markets.

We also find that farmers that are better connected with markets are able to manage the pandemic more effectively than farmers with limited access. This implies that efforts should be made to improve market linkages of the farmers. Our analysis shows that better market linkages will allow farmers to attract better prices and therefore provide incentive to improve agricultural practices.

We also find that quite a significant proportion of our farmers are dependent on middlemen for services such as informal credit and transport. Further, farmers who are

credit constrained and do not have ease of access to markets, and transact with unlicensed agents are most susceptible to fluctuations in market conditions. There is a need to relax farmers' constraints so that these farmers are able to fare better during difficult economic times.

Finally, this paper has focused on the upstream supply chain. It is equally important to understand the downstream effects in granular detail. As extension of this research, we are already working on mapping the downstream supply chains for multiple fresh produce in Punjab, Pakistan. This investigation will allow us to better understand the role played by agents from the wholesale to final consumer.

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Appendices

Appendix A - Farmer Survey Instrument Details

The instrument has 7 sections:

1. Demographic Details

This section asks basic demographic questions and agricultural land details, major crops harvested, and how the farmer sells his produce.

2. Agent Information

This section takes information of all different agents that the farmer sold their potato produce to. The information taken includes name, contact number, CNIC, business address and services provided by the agent,

3. Crop Information

This section takes all sowing and harvesting dates, total yield, and how and when they sold to their respective agents. Moreover, transaction details are noted if the farmer has sold in the market themselves or whether the farmer has sold to any firm/company.

4. Covid-19 Impact

This section asks about the impact that Covid-19 has had on the farmer and the role that middlemen played during Covid-19.

5. IT adoption

This section records information on any IT usage related to agriculture in the farmer's household and whether they are using specific apps developed for agricultural purposes. This section also records the farmer's view on the advantages and disadvantages of IT adoption in agriculture.

6. Financial Information

This section asks questions about financial information such as loans for personal and agricultural use and the types of institutions used in each case. This also records the reasons for not availing loans from formal institutions.

7. Social Networks

This section collects information regarding networks i.e., who does the farmer contact in cases of financial need, questions about agricultural practices etc.

Appendix B - Construction of COVID Composite Index

The Government Stringency Index takes a value from 0-100, with 100 being the strictest measures possible. The tracker allows for the policy responses across the world to be compared in a consistent and rigorous manner by creating a stringency index that aggregates a number of categories to calculate a national and subnational score.

The Google Community Mobility data relies on the location history of phones that use Google services to track movement of individuals. These data record the percentage changes to the number of visitors on a particular day of the week by comparing it with the median value of visitors on the same day of the week from before COVID spread globally. Google uses a five-week period for constructing the pre-covid baseline values for each day of the week by taking the median number of visitors for that day for the period January 3, 2020 to February 6, 2020. In this sense, there are 7 baseline values for each day of the week. This allows a baseline monday value to be compared with a monday that comes later after the spread of COVID. Since Google reports these data in terms of percentage changes, a value of +2 against a place category on Monday, April 20, 2020 implies that there were 2% more visitors to the place category compared to the median number of visitors on the baseline Monday. This is done for five of the six place categories: retail and recreation, groceries and pharmacies, parks, workplaces and public transit. For the last place category, 'residential' the number of visitors would not make sense so Google uses the number of hours spent to measure changes to this. For our analysis we exclude this last category since the unit is different and also we are interested in the movement of individuals to places that were restricted or closed due to lockdown. The smallest unit for which these data are available for Pakistan is major urban centres, of which six fall in the Punjab province.

There are two reasons for utilising the Google community mobility data along with the stringency index:

1. For the case of Pakistan, subnational stringency index scores are unavailable. We use the mobility data to introduce regional variation.

2. The Stringency index measures the strictness of announced protocols by the national Government. It does not necessarily indicate compliance with those restrictions. The actual movement of individuals, however, is a good estimate of the extent to which the population followed the announced measures of the government. The effect on the movement of individuals could be the outcome of enforcement by state functionaries (imagine shops, markets, schools being forced shut) or due to voluntary compliance (people are fearful of COVID and take precautionary measures themselves).

We calculate the composite index as stated below:

$$I_{tm} = G_t \cdot \frac{1}{\sum_i (P_{itm} + 100)}$$

$$I_t = Ln \left\{ \frac{\left(\frac{\sum_m I_{tm}}{m} \right)}{6} \right\}$$

I_t = *Composite Index at time t*

G_t = *Government Stringency Index*

P_i = *Value for percentage change of visitors to place category i on t compared with baseline*

m = *{Lahore, Faisalabad, Sialkot, Gujranwala, Sargodha, Multan}*

i = *{recreation, groceries and pharmacies, public transit, public parks, workplace}*

Appendix C - Pictures from Fieldwork

Farmer Survey Visit: Manga Hithar (*Mouzza)*, Lahore

Farmer Survey Visit: Harike Naul (*Kasur)*, Lahore

Farmer Survey Visit: Meerak (*Mouzza*), Okara

Potato Auction Visit: Badami Bagh Market, Lahore

Onion Auction Visit: Badami Bagh Market, Lahore

Onion Auction Visit: Badami Bagh Market, Lahore

Farmer Survey Visit: Bhasin (*Mouzza*), Lahore